Federal Reserve Bank of Minneapolis Quarterly Review
Vol. 20, No. 2, Spring 1996, pp. 16–33

Using Monthly Data to Improve Quarterly Model Forecasts

Preston J. Miller

Vice President and Monetary Adviser
Research Department
Federal Reserve Bank of Minneapolis

Daniel M. Chin

Portfolio Risk Analyst
First Bank System

Abstract

This article describes a new way to use monthly data to improve the national forecasts of quarterly economic models. This new method combines the forecasts of a monthly model with those of a quarterly model using weights that maximize forecasting accuracy. While none of the method's steps is new, it is the first method to include all of them. It is also the first method to be shown to improve quarterly model forecasts in a statistically significant way. And it is the first systematic forecasting method to be shown, statistically, to forecast as well as the popular survey of major economic forecasters published in the *Blue Chip Economic Indicators* newsletter. The method was designed for use with the quarterly model maintained in the Research Department of the Minneapolis Federal Reserve Bank, but can be tailored to fit other models. The Minneapolis Fed model is a Bayesian-restricted vector autoregression model.

The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

The time periods in most forecasting models of the national economy are quarters, not months or weeks or days. This choice of model frequency is natural since many of the most reliable data series on national economic activity—including the gross domestic product (GDP)—are not published for time periods finer than a quarter. Yet a lot of major national data are published more frequently—employment levels monthly, money measures weekly, and interest rates daily, for example. In fact, many quarterly data series are constructed from finer-time data. So finer-time data should be a source of useful information for anyone interested in analyzing economic activity in the current, incomplete quarter. But how should national forecasters with quarterly models use these finer-time data to improve their quarterly forecasts?

Few researchers in this area would disagree that, in theory, the best way to use these data is to build a single model that relates data of all frequencies. Unfortunately, though, building such a comprehensive model is very hard. It has been attempted (Zadrozny 1990), but so far not successfully.

Some researchers have tried, instead, to shift to a monthly model. This means that they have to construct monthly values of the data that are only available quarterly. (See, for example, Litterman 1984, pp. 6–7, and Corrado and Reifschneider 1986.) This method turns out to be helpful in updating forecasts of the current quarter based on incoming monthly data. However, it is not helpful in forecasting for much longer horizons. Our study suggests that for more than two quarters out, the most accurate forecasts come from a quarterly model.

What most forecasters do is to use two separate models. They keep their quarterly model and use as well some sort of monthly model to update it. The monthly model may be a highly formal mathematical structure or merely vague notions about how economic variables are related. Whatever its form, though, the monthly model produces updated forecasts of the current quarter. The quarterly model uses those forecasts as data for the current quarter and then forecasts the quarters beyond.

While this method of using two models to forecast is simple and worthwhile, it ignores two potential ways that quarterly forecasting accuracy could be improved. One is by using the quarterly model itself to forecast the current quarter. The other is by using the monthly model to forecast not just the current quarter, but also the following quarter. To exploit these possibilities, the forecasts from the two models must be combined using a formal method.

The method we try here combines the forecasts of two mathematical models—a quarterly model and a monthly model—using weights that maximize forecasting accuracy. This is not a new method; each of its steps has been tried by other studies (Corrado and Greene 1988; Corrado and Haltmaier 1988; Fuhrer and Haltmaier 1988; Howrey, Hymans, and Donihue 1991; and Rathjens and Robins 1993). But no other study has incorporated all the steps. And we are the first to show, using the test of Christiano (1989, pp. 16–17), that our method improves quarterly forecasts in a statistically significant way.

Furthermore, we are the first to show that a systematic forecasting model can compete with the popular *Blue Chip Economic Indicators*, a newsletter which publishes the results of a monthly survey of major economic forecasters. The *Blue Chip* consensus forecast is not based on a mathematical model and so is not easily reproducible or its procedures improved by researchers. But this survey does provide monthly updates of quarterly forecasts, and it has a good track record which no model has been shown to match—until now. According to the Christiano test, the forecast errors made by our method of combining quarterly and monthly model forecasts are statistically no different than those made by the *Blue Chip* survey.

The Method and the Models

General Methodology

Before describing our particular models, let's look more closely at our general methodology. Again, we use two separate forecasting models—one quarterly and one monthly—and then combine their forecasts. Both our models are vector autoregression (VAR) models. Coefficients of the monthly model are estimated at three roughly equally spaced dates in the quarter. The forecasts from the two models are combined at each of these dates. The forecasts are combined using an ordinary least squares regression, which in our case minimizes forecast errors.

☐ *Forecasting the Current Quarter*

For expositional purposes, we can describe our method of forecasting the current quarter, t, as including the following steps:

1. Run the quarterly VAR forecasting model based on data through the previous quarter, X_{t-1}, X_{t-2}, ..., to get a forecast,

$$\hat{X}_t^Q = Q(X_{t-1}, X_{t-2}, ...) \tag{1}$$

   where Q gives the quarterly model's forecast of quarterly data.

2. Use a VAR model for relevant monthly data, $M_{t:i}$, to predict the data for each month in quarter t, where i is the number of months of data available in quarter t. For instance, when two months of data are available, the forecast of the third month is

$$\hat{M}_{t:3} = M(M_{t:2}, M_{t:1}, M_{t-1:3}, M_{t-1:2}, ...) \tag{2}$$

   where M gives the monthly model's forecast of current-quarter monthly data.

3. Predict the current quarter's data, X_t, from the monthly data, both actual and predicted. For instance, when two months of data are available in quarter t, this forecast is

$$\hat{X}_t^M = m(\hat{M}_{t:3}, M_{t:2}, M_{t:1}) \tag{3}$$

   where m gives the forecast of current quarterly data based on monthly values of variables through the end of the quarter, actual and estimated.

4. Combine $\hat{X}_t^Q$ and $\hat{X}_t^M$ by using them as inputs in a regression estimated through $t - 1$ to get the method's current-quarter estimate:

$$\hat{X}_t = a_0^j + a_1^j \hat{X}_t^Q + a_2^j \hat{X}_t^M \tag{4}$$

where j is the number of months of current-quarter data available. Estimate the a's—the coefficients, or *weights*—given the data available at the dates of j = 1, 2, or 3.

(In practice, steps 3 and 4 above are combined, and regressions are run of quarterly averaged variables on their quarterly model predictions and quarterly averaged values of relevant monthly series, both actual and predicted from the monthly model.)

We expect the estimated values of the weights on the monthly based forecast, the a_2's, to be different from zero. This is because steps 2 and 3 are intended to mimic what the U.S. Bureau of Economic Analysis (BEA) does when it estimates GDP. The BEA estimates GDP using a lot of other time series, many of which are published monthly. When a quarter's first estimates of GDP are made, not all those monthly data series are available yet. So the BEA first fills in the values of missing monthly data in a manner analogous to our step 2. Then, given a complete set of monthly data, actual and predicted, the BEA forms estimates of GDP and GDP components in a manner analogous to our step 3. Thus, we would expect the value of our a_2's to approach one the closer we come to replicating the BEA's procedures.

But why should the estimated values of the weights on the quarterly based forecast, the a_1's, be different from zero? If the BEA's estimates of current-quarter GDP are based on current-quarter monthly data, why should forecasts be useful from a quarterly model that ignores all these data? Three reasons come to mind:

- Even when all the data for a quarter are available, the data used in a small monthly VAR model are just a small subset of the data used by the BEA.
- At the time of the BEA's first estimate of GDP, the data on current-quarter monthly series are incomplete. The predictions of the missing data will be different for the BEA and for the monthly VAR model.
- Through much of the quarter, the monthly VAR model must be used to predict values of missing monthly data that the BEA will have when it issues its initial GDP estimate.

For all these reasons, a small monthly VAR model will make errors in predicting current-quarter GDP. These errors are likely to be larger the sparser are the current-quarter data. Thus, predictions of current-quarter GDP from a quarterly model might contain useful information, especially when little current-quarter data are available.

☐ *Forecasting the Next Quarter*

Our approach for the current quarter lets the data decide the weights to put on the forecasts of the quarterly and monthly models. We could simply condition the quarterly model on the updated forecast for the current quarter to generate forecasts for all future quarters. However, there are two good reasons to think that the monthly model will also be useful in forecasting the next-quarter values. One reason is conceptual; the other, empirical.

On conceptual grounds, note that since the quarterly model forecast for quarter $t + 1$ is conditioned on the combined updated forecast for quarter t, the quarterly model already uses current monthly data in quarter t. However, the monthly data enter in a very restricted way. The dynamic structure of the quarterly model determines quarter $t + 1$ outcomes. The question is whether quarter t monthly data contain more information for quarter $t + 1$ outcomes than is captured by the quarterly model.

Intuition suggests they do. Suppose a series follows a random walk from month to month. Suppose three months of data are available in quarter t. Then clearly a better forecast for this series in quarter $t + 1$ can be made using the value of the series in the last month of quarter t rather than using the quarterly average in quarter t. If only two months of data were available in quarter t, some forecasting improvement for quarter $t + 1$ could still be expected by using the value of the series in the middle month of the quarter rather than the quarterly average generated from the first two months of data. That is, for the monthly random walk series X, the best forecast of X_{t+1} given $X_{t:1}$ and $X_{t:2}$ would be $X_{t:2}$ from the monthly model and $(X_{t:1} + 2X_{t:2})/3$ from the quarterly model. However, by this argument, the forecasts of the series for quarter $t + 1$ given only one month of data in quarter t would be the same using either the monthly or the quarterly model, namely, $X_{t:1}$. Thus, this conceptual exercise suggests that the monthly data in quarter t are useful for predicting quarter $t + 1$ outcomes, but that the usefulness declines as the amount of monthly data in quarter t declines, approaching zero with only one month of data.

Simple regressions seem to support this conceptual argument. For instance, we run regressions of GDP in quarter $t + 1$ on a constant, on the quarterly model's forecast of GDP in quarter $t + 1$ conditioned on the updated forecast for quarter t, and on the monthly model's estimate of the index of hours worked by production workers in quarter $t + 1$. With three months of data available in quarter t, the coefficient on the monthly model prediction of hours worked in quarter $t + 1$ is significantly different from zero to a high degree (at level 0.0009). With two months of data available in quarter t, the coefficient is still significant, but less so (at level 0.0217). With only one month of quarter t data, the coefficient is not statistically significant (at level 0.3894). We get similar results from running regressions for other series. In addition, Rathjens and Robins (1993) find that the monthly pattern of a time series in quarter t can be useful in forecasting the quarterly average of that series in quarter $t + 1$.

Based on these findings, we extend the general approach to incorporating finer-time data by using an analogous procedure to update forecasts of quarterly data in quarter $t + 1$. Specifically, we add these steps:

5. Forecast $\hat{X}^Q_{t+1}$ from the quarterly model using the combined forecast for X_t from step 4:[1]

$$\hat{X}^Q_{t+1} = Q(\hat{X}_t, X_{t-1}, \ldots). \tag{5}$$

6. Use the monthly model to predict values for each month in quarter $t + 1$; for instance, to predict data for the second month of $t + 1$, $M_{t+1:2}$, given the data through the second month of quarter t, $M_{t:2}$, use

$$\hat{M}_{t+1:2} = M(\hat{M}_{t+1:1}, \hat{M}_{t:3}, M_{t:2}, M_{t:1}, \ldots). \tag{6}$$

7. Predict X_{t+1} based on the predicted monthly data:

(7) $\hat{X}^M_{t+1} = m(\hat{M}_{t+1:3}, \hat{M}_{t+1:2}, \hat{M}_{t+1:1})$.

8. Derive the combined forecast for X_{t+1} from a regression estimated through $t - 1$:

(8) $\hat{X}_{t+1} = b^j_0 + b^j_1 \hat{X}^Q_{t+1} + b^j_2 \hat{X}^M_{t+1}$

where the coefficients are estimated given the data available at three dates, j = 1, 2, or 3, in quarter t. (Our prior is that when j = 1, the combined forecast $\hat{X}_t$ contains all the information in $M_{t:1}$ that is useful in predicting $\hat{X}_{t+1}$.)

Particular Models

Although our method can be adapted for use with any quarterly model, it was designed for use with the quarterly model maintained in the Research Department of the Minneapolis Federal Reserve Bank. In order to describe our method in concrete terms, we describe this specific application. Determining how to tailor the method to fit other quarterly models is straightforward.

Our quarterly model contains quarterly averages of time series available at both quarterly and finer-time frequencies. (See Table 1.) Column (1) of Table 1 is a list of the model's quarterly time series taken from the national income and product accounts (NIPA). All the NIPA data are in 1987 dollars and are based on implicit price deflators rather than chain-weighted deflators. Column (2) is a list of the other time series the model uses, which are averaged to get quarterly values. These are series that are available monthly or at even finer-time intervals, but all their quarterly averages are computed as the averages of the monthly values for the three months in the quarter. For instance, even though the federal funds rate is available daily, first a monthly series is computed as monthly averages of daily values, and then quarterly averages are computed as the arithmetic averages of the three monthly values in each quarter.

The quarterly model is a Bayesian-restricted VAR. The Bayesian restrictions reduce to choices of hyperparameter values. The choices are made to maximize out-of-sample forecasting accuracy according to an explicit criterion, and the procedure used to choose the values is provided in Doan 1992.

Our method updates the quarterly model's prediction based on available monthly data at three dates in the quarter.[2] We use the three dates on which the U.S. Department of Labor releases employment data. (These are, roughly, the first Friday of each month.) Our monthly data set includes all the series listed in columns (2) and (3) of Table 1. The series in column (3) were chosen to improve the predictions of GDP and its components. These series (perhaps in combination) had coefficients with significant t-scores and improved the fit of our updating equations for GDP and its components.

Test Results

We judge the usefulness of our method by making two types of comparisons. First we compare the forecasting accuracy of our quarterly model with and without monthly updating. This comparison suggests how much any quarterly model could gain by using finer-time data—which is a lot. Then we compare the forecasting performance of our updated quarterly model to that of the *Blue Chip* survey.[3] This comparison is intended to determine if our simple mechanical method can compete with more ad hoc, judgmental methods. It can.

With vs. Without Monthly Updating

☐ *Potential Gain*

The main avenue for gain from incorporating monthly data into quarterly models would seem to be by improving accuracy in predicting the current quarter. The largest potential gain along this avenue is, of course, perfect accuracy. If our method of incorporating monthly data did that well, then obviously it would greatly improve one-step-ahead forecasts. The question is, Can perfect accuracy for the current quarter help the model forecast further into the future?

To try to answer this question, we do a simple exercise. First we measure the forecast errors the model makes over time when it has no data for the current quarter. Then we essentially give the model all the data for the current quarter, so it can predict the quarter perfectly, and we measure the errors it now makes in future quarters.

To get the first set of errors, we start by estimating the quarterly model over the period from the first quarter of 1959 through the first quarter of 1979 (1959:1–1979:1) and generate dynamic forecasts for the next eight quarters. We then incorporate the actual values for 1979:2 into the sample period, reestimate the model, and again generate one-through eight-step-ahead dynamic forecasts. We repeat this procedure through 1993:1 to forecast the period 1993:2–1995:1. We thus get a total of 60 forecast errors for horizons of up to eight quarters. Next we compute root mean squared errors (RMSEs) for all the time series in the quarterly model at each horizon. We measure the errors in terms of growth rates for all series expressed as levels and in terms of actual units for all other series—those expressed as differences, such as the change in inventories and net exports, and those expressed as rates, such as the unemployment rate and interest rates. These errors indicate the forecasting accuracy of the quarterly model for horizons of one through eight quarters when the forecasts are based on actual data through quarter 0.

To get the second set of forecast errors, we estimate and forecast as before, but we condition the forecast on the actual values for the current quarter. Hence, by assumption, the one-step-ahead forecast errors here are zero. We then generate forecast errors for future quarters conditional on the current, perfectly accurate forecast for quarter 1.

In Charts 1–5, we display a sampling of the results of this exercise. (For the rest, as well as for detailed results from our other exercises, see Miller and Chin, forthcoming.) In the charts, for five of the quarterly model's time series, we plot the RMSEs of the forecasts for horizons of two through eight quarters assuming either that the model has data through quarter 0 (an *unconditional* forecast) or that the model's forecasts of quarter 1 are perfectly accurate (a *conditional* forecast). Among all the model's time series, when the current quarter is hit on the nose, the forecasts of more than half of the series improve at all horizons. The forecasts for the civilian unemployment rate (Chart 4) and the consumer price index (Chart 5) are examples of that. Among the other series, the forecast for GDP (Chart 1) is typical. It improves mainly in the two quarters after the current quarter, with little difference beyond that. This exercise demonstrates that perfect accura-

cy for the current-quarter forecast can potentially help the model forecast most time series further into the future.

Current-Quarter Gain

But how much does our monthly updating method actually help? To examine that, we start by examining the current-quarter forecasts. We compare the forecasting accuracy for the current quarter t from the quarterly model based on quarterly data through $t - 1$ with that of the best combined (monthly updated) forecasts for t based on data available at each of the three employment release dates between the $t - 1$ and t advance GDP releases. We estimate the models from 1959:1 through 1978:4, forecast for 1979:1, reestimate through 1979:1, forecast for 1979:2, and repeat, to generate 65 quarter t forecasts. We summarize the errors by Theil's U statistics, mean absolute errors, and RMSEs.[4]

The results for a sample of five series are displayed in Table 2. These are representative of the results for all the quarterly model's time series. In general, the monthly data significantly improve the forecasts of current-quarter series, and the more complete the monthly data, the better. For instance, the Theil U for the GDP growth rate in the current quarter is 0.805 for the quarterly model. That drops to 0.647 for a combined forecast with one month of current-quarter hours-worked data and no current-quarter months of consumption data.[5] The Theil U drops further, to 0.465, when another month of hours-worked data and one month of consumption data are added. Finally, a combined forecast with three months of current-quarter hours-worked data and two months of current-quarter consumption data takes the Theil U down to 0.459.

We use Christiano's (1989, pp. 16–17) test to determine the significance of the differences between RMSEs from the combined forecasts and those from the quarterly model's forecast.[6] The improvement in forecasting performance is highly significant for nearly all the series.

Overall, then, the forecasts of most quarterly model series improve by using current-quarter monthly data. The improvement for series that are available monthly is large, even when only one month of current-quarter data is available.

There are some notable exceptions to this general improvement in forecasting accuracy:

- *Consumption of durable goods.* The forecasts of consumption durables are slightly worse using current-quarter monthly data when only one month of employment data is available. This basically reflects the facts that current-quarter consumption data are not available at the time of the first employment release and that the combined forecasts for consumption give zero weight to the quarterly model forecast. (This is required by our sequential estimation procedure; see the Appendix.) Thus, the comparisons reveal that the quarterly model based on complete information for quarter $t - 1$ does slightly better than a (univariate) monthly model based on complete monthly data for consumption in quarter $t - 1$.
- *Federal government purchases.* Current-quarter monthly data, as they become more complete, do not help forecast federal government purchases.[7] This is because movements in federal purchases are dominated by movements in defense purchases, and the relationship between that series and its primary monthly data source is unstable.

  The primary monthly data source for defense purchases is the defense outlay series in the monthly U.S. Treasury report. This monthly series is on a payments basis and must be transformed into an accrual basis (which, for example, puts into the first quarter a government check mailed in April for an expense incurred in March). For some reason, in the mid-1980s, defense outlays began to be much more volatile, and the relationship between these outlays and all federal government purchases shifted; the quarterly contemporaneous correlation between the series was 62 percent between 1975 and 1986, but only 14 percent between 1987 and 1994.

  This change is clear in Chart 6, which plots the two series. The chart also demonstrates why a monthly series can improve the fit of an equation over a sample period as a whole, yet not improve forecasting accuracy over just a part of it.

In Charts 7–11, we contrast the errors made by the quarterly model without any monthly updating and those made by the combined method with progressively more months of data. In the charts, for five of the quarterly model's time series, we accumulate one-step-ahead absolute forecast errors between 1979:1 and 1995:1. These charts give a visual display of how much current-quarter data improve forecast accuracy in the current quarter. While the charts essentially reinforce the conclusions reached with Table 2, they also show in which periods forecasts went astray and how regularly one forecast outperforms another.

Next-Quarter Gain

Now we see how much monthly updating in the current quarter can improve forecasts of the next quarter. According to our method, current-quarter data in quarter t affect forecasts of quarter $t + 1$ in two ways. First, they are used to generate updated forecasts for quarter t, which are then used to condition the quarterly model's forecasts for quarter $t + 1$ (step 5). Second, the monthly model uses current-quarter data to forecast monthly values of series which enter into the combined forecasts for quarter $t + 1$ (steps 6–8). The first of these uses turns out to improve forecasting accuracy for the next quarter. But, surprisingly, the second use does not.

Table 3 shows the value of using monthly updates to condition the quarterly model's forecasts. For our five selected time series, the table compares the forecasting accuracy of the quarterly model for quarter $t + 1$ when the model has available zero, one, two, or three months of employment data in quarter t. When some quarter t data are available, the best combined forecasts for quarter t are generated, and they are used to condition the quarterly model's forecast for quarter $t + 1$. Due to restrictions from our sequential estimation method (described in the Appendix), forecast errors are generated over the fairly short period 1989:1–1995:1.

The results in Table 3 are representative. In general, there is a modest gain in forecast accuracy for quarter $t + 1$ from conditioning the quarterly model's $t + 1$ forecasts on updated forecasts for quarter t. The gain for GDP and its components is small and, in some cases, nonexistent. However, the gain for some of the monthly series is quite large.

For instance, using monthly data available in the third month cut the forecast errors for the unemployment rate in half.

We next examine whether the conditioned quarter $t + 1$ forecasts from the quarterly model can be improved by combining them with the forecasts of monthly series in quarter $t + 1$ from the monthly model. A comparison of Table 3 and Table 4 shows that they cannot: combining the forecasts offers no additional value from what is gained by conditioning the quarterly model forecasts on the updated quarter t forecasts.

Why should this be? It seems to contradict an earlier result. Recall that we ran a regression of actual GDP in quarter $t + 1$ on the quarterly model's updated forecast of GDP in quarter $t + 1$ and the monthly model's forecast of hours worked in quarter $t + 1$, where the updates were based on three months of current-quarter employment data. In that exercise, the hours-worked series enters with a highly significant coefficient and improves the fit of the regression. Yet here we have seen that with three months of current-quarter data, the combined next-quarter forecast for GDP is no better than the updated quarterly model forecast.

Our investigation of this phenomenon focuses on how the coefficients on the updated model's forecasts of GDP and hours worked change over time. We estimate the same regression over the period 1979:2 through 1983:4 and record the coefficients. We then add an observation, reestimate, and record the coefficients. We continue this process through 1994:4 and then plot the time path of the coefficients in Chart 12. A clear pattern emerges: over the last part of the estimation period, from 1983:4 until 1988:4, the relationship between GDP and the hours-worked forecast was stable, but the relationship between GDP and the GDP forecast was not. However, over the forecast period, from 1989:1 until 1994:4, the situation is reversed; the GDP relationship is stable, while the hours-worked relationship is not. Relative stability of the hours-worked relationship over the whole sample period, 1979:2–1994:4, explains why that series enters significantly and improves the fit of the regression. The instability of that relationship over the period from 1989:1 on explains why inclusion of that series worsens forecast performance.

We conclude that we need more observations than are now available to determine whether the instability in the GDP–hours-worked relationship for quarter $t + 1$ is a one-time or a recurring phenomenon. If it proves to be one-time, the usefulness of using our monthly forecast of hours worked in quarter $t + 1$ should become apparent. But if it proves to be recurring, the best forecast for GDP in quarter $t + 1$ will be the updated quarterly model forecast. We suspect that with more observations the contradiction between the two results on regression fit and forecasting accuracy will be resolved one way or the other.

Our Method vs. Blue Chip'*s*

Now we compare the accuracy of our combined model forecasts to that of the leading judgmental forecasts, the *Blue Chip* survey's. To make this comparison valid, we must use our method to produce, as much as possible, forecasts based on only the data that were available at the time that the *Blue Chip* survey forecasts were made. This type of forecast is known as a *real-time* forecast.

Because the construction of real-time forecasts is so time-consuming, we limit the comparison to three key series: the annual growth rate of GDP, the annual growth rate of the consumer price index, and the quarterly rate of civilian unemployment. We compare the forecasts when one, two, and three months of employment data are available.

The construction of real-time *Blue Chip* forecasts is straightforward. By definition they are the forecasts that *Blue Chip* released with a one-month lag. That is, the *Blue Chip* consensus forecast issued in one month is based on data that were available one month earlier.

The construction of our real-time forecasts is more complicated. First we construct a data bank which holds for each time series only the values of the series that were available at the time the *Blue Chip* forecasts were made. Then, at each employment release date, we estimate our models and forecast the current quarter based on the data that would have been available at the time.

Table 5 compares these real-time forecasts. It shows that over the period 1990:1–1995:3, the differences in forecasting performance between the *Blue Chip* survey and our method were quite small. In fact, according to Christiano's (1989, pp. 16–17) test, none of the differences in RMSEs is statistically significant.

Conclusion

Some might ask, Why go to all the bother of formally updating quarterly model forecasts? After all, the *Blue Chip* survey of major economic forecasters already provides monthly updates of quarterly forecasts, and it has a very good record. We see three distinct advantages to using our method instead of the *Blue Chip* survey:

- *Timeliness.* Our method allows forecast updates as soon as the monthly data are published. The *Blue Chip* survey updates take more than a month to prepare: the individual survey forecasts must be revised to incorporate the new data, the revised individual survey forecasts must be compiled and combined, and the resulting tables must be published and distributed.
- *Potential for improvement.* Our method is reproducible by other researchers and so has the potential to be improved by them. After examining our models, for instance, other researchers might discover better ways to identify or estimate them. The *Blue Chip* consensus forecast incorporates many judgmental forecasts that cannot be improved by other researchers because no one but the forecasters themselves knows precisely how they were made.
- *Ability to do conditional forecasts.* Our method can be used to generate forecasts conditional on some future event, such as a specified change in monetary policy one month ahead. The *Blue Chip* consensus forecast is unconditional and cannot be used in this way.

Of course, these advantages to using our method rather than *Blue Chip*'s apply as well to other model-based updating methods. However, only our method incorporates all the updating steps, and only ours has been shown to improve forecasting accuracy in a statistically significant way.

*Formerly Economic Analyst, Research Department, Federal Reserve Bank of Minneapolis.

[1]Corrado and Haltmaier (1988) base the quarterly model's forecast for quarter $t + 1$ on the quarterly model's forecast for quarter t rather than on the best combined forecast

for quarter t. That is, in their version of equation (5), they have $\hat{X}_t^Q$ rather than $\hat{X}_t$. However, by construction, $\hat{X}_t$ is a more accurate forecast.

[2]For a detailed technical description of how we use the method with the model maintained at the Minneapolis Fed, see the Appendix.

[3]For the first type of comparison, we use data available as of August 16, 1995. For the second, we use data for the period from the first quarter of 1990 through the third quarter of 1995.

[4]The Theil U statistic is calculated as the ratio of the RMSE of the forecast from our model to the RMSE of a naive forecast of no change. If our model's forecast is adding value, then the ratio should be less than one.

[5]When the employment data are released, there is a lag of one month in the availability of consumption, the industrial production index, the consumer price index, and the monetary base. The other financial series are available with no lag.

[6]Researchers have disparaged the R^2 statistic because its distribution is unknown. Christiano (1989, pp. 16–17) has pointed out that although we don't know the distribution of R^2 from a given model, we do know the approximate distribution of the differences in R^2's from two different models. Based on this approximate distribution, the Christiano procedure lets us test the statistical significance of differences in R^2's from our method and other methods.

[7]The combined forecast of net exports does worse than the quarterly model (or a naive no-change forecast) no matter how much current-quarter data are available. This outcome is not surprising, since the quarterly model forecasts net exports directly, while the combined forecast treats this component as a residual, the difference between GDP and the sum of the other components. Thus, in the combined forecast, net exports picks up the errors in forecasting GDP and all other components.

Appendix
A Closer Look at Our Updating Method

Here we describe in more detail our method for updating quarterly model forecasts with monthly data, which is discussed in the preceding paper.

Predict Missing Monthly Data

The first step in our method is to obtain missing values for monthly series when data are not available for all the months in a quarter. We predict missing monthly values using a large Bayesian vector autoregression (BVAR) model with a lot of zero restrictions. The restrictions break the model into submodels which are themselves either BVARs or autoregressions (ARs), each with six lags on each series. In all our regressions, series are logged, except when series are expressed as differences or rates.

Table A1 lists the monthly series in our models, along with their sources and their standard abbreviations, which we shall use here. Each of the two main groups of series—the production sector and the nominal sector—is modeled as a BVAR. All the other series are modeled as ARs.

Among those other series are two that must be adjusted to get updated constant-dollar values before they are used to update related national income and product account (NIPA) series. The two series are adjusted in different ways:

- *Total business inventories* are generally reported as constant-dollar values, *TBIR*, for month $m - 2$ and preceding months and as current-dollar values, *TBI*, for month $m - 1$ and preceding months. We compute a value for *TBIR* for month $m - 1$ as

(A1) $$\widehat{TBIR}_{m-1} = TBI_{m-1}/\widehat{TBID}_{m-1}$$

where $\widehat{TBID}_{m-1}$ is the estimated value of the implicit deflator for the stock of business inventories. To estimate $\widehat{TBID}_{m-1}$, we first generate historical series for $m - 2$ and earlier, using the identity $TBID_t \equiv TBI_t/TBIR_t$. We then estimate $\widehat{TBID}_m$ using the producer price index, *PPI*, and the regression

(A2) $$\widehat{TBID}_{m-1} = \hat{A}(L)TBID_{m-2} + \hat{B}(L)PPI_{m-1}$$

where $\hat{A}$ and $\hat{B}$ are lag distributions of order 6 and 7, respectively, and are estimated by the method of ordinary least squares (OLS) over the sample period from January 1959 to month $m - 2$ of the current year. We then use an autoregression for *TBIR* to fill in the remaining months.

- *Federal government outlays for national defense* are reported seasonally unadjusted in current dollars. We first use the U.S. Census Bureau's X-11 program to seasonally adjust the series. We then use an autoregression to fill in the missing months. We next convert the estimated nominal seasonally adjusted value for the quarter to constant dollars using an estimate for the defense purchase deflator for the quarter, $\widehat{DEFPD}_t$. We compute $\widehat{DEFPD}_t$ using a regression with four own lags, where past values are taken from the latest report on the gross domestic product (GDP), and with the current estimated value of the producer price index:

(A3) $$\widehat{DEFPD}_t = \hat{A}(L)DEFPD_{t-1} + \hat{b}\widehat{PPI}_t$$

where $\hat{A}$ and $\hat{b}$ are estimated by OLS over the sample period from the first quarter of 1972 to quarter $t - 1$.

Once we have a complete set of monthly data for a quarter, computing quarterly averages is straightforward.

Update and Combine Model Forecasts

In order to complete our updating process, we combine two steps described in the preceding paper. One of those is step 3 in the paper: Predict quarterly values for all series in the quarterly model based on the estimated values found in the previous step for the monthly series. The other step is step 4 in the paper: Let the data decide for given amounts of current-quarter data how much weight to give to predictions from the quarterly model and the monthly model.

The Current Quarter

For the current quarter, we estimate regressions of the form of the paper's equation (4):

(A4) $$\hat{X}_t = a_0^j + a_1^j\hat{X}_t^Q + a_2^j\hat{X}_t^M.$$

For the monthly series in the quarterly model, we simply impose the restrictions $a_0^j = 0$, $a_1^j = 0$, $a_2^j = 1$ for $j = 1$, 2, or 3 months of employment data. That is, we estimate the quarterly values of the monthly series based solely on the projections of their respective monthly BVARs. Actually, no matter at what date we are in the quarter, we base projections on all available monthly data relevant to the monthly BVARs. Thus, for example, our projection of the industrial production index might be conditional on two months of data on the index of hours worked by production workers and the civilian unemployment rate and on only one month of the industrial production index itself. However, the coefficients are fixed for the whole quarter. In contrast, when we update the NIPA quarterly series, we do three separate regressions based on the data available at the times of the three current-quarter releases of the employment report.

The updates of NIPA estimates for the current quarter essentially follow steps 1–4 in the paper, with no restrictions on the a_i^j's. Since the particular procedures for the series vary, we discuss each in turn. (The NIPA series are listed, along with their standard abbreviations, in Table A2.)

☐ *Consumption*

We begin with the consumption series. In order to make best use of monthly data, we directly predict personal consumption expenditures, *C*, and consumption of durable goods, *CD*, and then compute consumption of nondurable goods and services, *CND*, as the difference: $C - CD$. Our method with respect to the consumption series necessarily differs from that with respect to other demand components because the consumption series are the only NIPA series reported monthly. We include a measure of real re-

tail sales—total (*RET*) or durables (*RETDUR*)—as an independent variable because for roughly half of each quarter, there is one more month of retail sales data than consumption data.

Thus, we use these monthly consumption regressions:

$$\text{(A5)} \quad \hat{C}_m = a + \sum_{i=1}^{6} b_i C_{m-i} + \sum_{i=0}^{6} c_i (RET_{m-i}/CPI_{m-i})$$

$$\text{(A6)} \quad \hat{CD}_m = d + \sum_{i=1}^{6} e_i CD_{m-i} + \sum_{i=0}^{6} f_i (RETDUR_{m-i}/CPI_{m-i})$$

where *CPI* is the consumer price index and the unit of time *m* is a month. The regressions predict C_m and CD_m given actual data for all right-side series. Predictions for C_{m+1} and CD_{m+1} are then based on actual data and the predictors for C_m, CD_m, RET_{m+1}, and CPI_{m+1}. This procedure is repeated sequentially if more months of predictions are required.

☐ *GDP*

We next directly update the GDP series. Since this is a series of primary interest, we improve its prediction by including it in the set of regressions rather than by excluding it and computing it as the sum of demand components. This means we must choose one demand component to be determined as a residual. For that, we choose net exports, *NX*, because monthly data related to that quarterly series are reported with a long lag and are often substantially revised.

In order to update the GDP forecast from the quarterly model prediction $\hat{GDP}^Q$, we use current data on *C* and hours worked, *HOURS:*

$$\text{(A7)} \quad \hat{GDP}_t = a^j + b^j \hat{GDP}_t^Q + c^j \hat{C}_t + d^j \hat{HOURS}_t$$

where the unit of time *t* is a quarter. We run separate regressions depending on whether we have *j* = 1, 2, or 3 months of current-quarter employment data.

Our update for GDP depends on our prediction for consumption. This implies a recursive structure for estimation. The sample period for the consumption equation begins in January 1959 while the sample period for the GDP equation begins in the first quarter of 1969. For example, to get the data point for the GDP equation for the first quarter of 1990, we first estimate the consumption regression over the period from January 1959 to the current month of data in the quarter and then use its resulting prediction for consumption in the first quarter of 1990 in the regression for real GDP.

☐ *Other Series*

We use our updated estimate of GDP as an explanatory variable for the rest of the demand components. This, then, implies a recursive structure for GDP and its components. Since our predictions of the components depend on our predictions of GDP, the regressions for the components must allow some start-up time to generate the GDP predictions. Our component regressions are estimated over the sample period beginning in the first quarter of 1974. (Table A3 summarizes the estimation and forecast periods for GDP and its components.)

For the investment series, we directly predict fixed investment, *FI*, and change in business inventories, *CBI*, and compute total investment, *I*, as their sum. In particular, our regressions are of these forms:

$$\text{(A8)} \quad \hat{FI}_t = a^j + b^j \hat{FI}_t^Q + c^j (\hat{SHIP}_t/\hat{PPICG}_t) + d^j \hat{VNCP}_t + e^j \hat{GDP}_t$$

$$\text{(A9)} \quad \hat{CBI}_t = a^j + b^j \hat{CBI}_t^Q + c^j (\hat{TBIR}_{t:3} - TBIR_{t-1:3}) + d^j \hat{GDP}_t$$

where *SHIP* is shipments of nondefense capital goods, *PPICG* is the producer price index of capital equipment finished goods, *VNCP* is the real value of new private construction put in place, and *j* = 1, 2, or 3 months of current-quarter employment data.

For the government series, we directly predict federal government purchases, *GF*, and state and local government purchases, *GSL*, and compute total government purchases, *G*, as their sum. The regressions take these forms:

$$\text{(A10)} \quad \hat{GF}_t = a^j + b^j \hat{GF}_t^Q + c^j (\hat{NATDEF}_t/\hat{DEFPD}_t) + d^j \hat{IPDS}_t + e^j \hat{GDP}_t$$

$$\text{(A11)} \quad \hat{GSL}_t = a^j + b^j \hat{GSL}_t^Q + c^j \hat{VNCSL}_t + d^j \hat{GDP}_t$$

where *NATDEF* is federal government outlays for national defense, *IPDS* is the industrial production index of defense and space equipment, *VNCSL* is the real value of new state and local government construction put in place, and *j* = 1, 2, or 3 months of current-quarter employment data.

The Next Quarter

Our procedure for updating forecasts in quarter *t* + 1 given current-quarter data for quarter *t* is more or less that for updating forecasts in quarter *t*. First we use the procedure described above to generate for quarter *t* updated predictions of all series in the quarterly model. Then we treat these updated forecasts as actual data in the quarterly model, estimate the quarterly model through quarter *t*, and generate forecasts from that model for quarter *t* + 1.

Our updating equations for quarter *t* + 1 forecasts of the quarterly model series are of the same form as those for the quarter *t* forecasts, with three minor exceptions. One exception is that the prediction of quarter *t* + 1 GDP for the regressions of demand components is not based on the monthly time series for consumption. Instead, when we compute the value of GDP_{t+1} that appears in those regressions, we restrict c^j to be zero. This is because we found that the forecast of C_{t+1} from our monthly model does not improve the quarterly model's forecast of GDP_{t+1}. Another exception is that in the quarter *t* + 1 forecasts, predicted values of own series for all demand components from the quarterly model are based on updated values for all series in quarter *t*, $\hat{X}_t$, not just from $\hat{X}_t^Q$. A third exception is that quarter *t* + 1 updates for the quarterly model's monthly series are based not only on the predictions from monthly ARs or BVARs, but also on the quarterly model forecasts for those series based on $\hat{X}_t$.

References

Blue Chip Economic Indicators: What Top Economists Are Saying About the U.S. Outlook for the Year Ahead. Various dates. Alexandria, Va.: Capitol Publications, Inc.

Christiano, Lawrence J. 1989. *P**: Not the inflation forecaster's Holy Grail. *Federal Reserve Bank of Minneapolis Quarterly Review* 13 (Fall): 3–18.

Corrado, Carol A., and Greene, Mark N. 1988. Reducing uncertainty in short-term projections: Linkage of monthly and quarterly models. *Journal of Forecasting* 7 (April-June): 77–102.

Corrado, Carol A., and Haltmaier, Jane. 1988. The use of high-frequency data in model-based forecasting at the Federal Reserve Board. Finance and Economics Discussion Series 24. Division of Research and Statistics, Board of Governors of the Federal Reserve System.

Corrado, Carol A., and Reifschneider, D. 1986. A monthly forecasting model of the United States economy. Manuscript. Board of Governors of the Federal Reserve System.

Doan, Thomas A. 1992. *Regression analysis of time series: User's manual.* RATS version 4. Evanston, Ill.: Estima.

Fuhrer, Jeffrey C., and Haltmaier, Jane T. 1988. Minimum variance pooling of forecasts at different levels of aggregation. *Journal of Forecasting* 7 (January-March): 63–73.

Howrey, E. Philip; Hymans, Saul H.; and Donihue, Michael R. 1991. Merging monthly and quarterly forecasts: Experience with MQEM. *Journal of Forecasting* 10 (May): 255–68.

Litterman, Robert B. 1984. Above-average national growth in 1985 and 1986. *Federal Reserve Bank of Minneapolis Quarterly Review* 8 (Fall): 3–7.

Miller, Preston J., and Chin, Daniel M. Forthcoming. Improving quarterly model forecasts using monthly data. Research Department Staff Report. Federal Reserve Bank of Minneapolis.

Rathjens, Peter, and Robins, Russell P. 1993. Forecasting quarterly data using monthly information. *Journal of Forecasting* 12 (April): 321–30.

U.S. Department of the Treasury. Various dates. *Monthly Treasury Statement of Receipts and Outlays of the United States Government.* Washington, D.C.: Government Printing Office.

Zadrozny, Peter. 1990. Estimating a multivariate ARMA model with mixed-frequency data: An application to forecasting U.S. GNP at monthly intervals. Center for Economic Studies Discussion Paper 90-5. Bureau of the Census, U.S. Department of Commerce.

Table 1

The Time Series in the Two Models

Quarterly Model	Monthly Model	
(1) Quarterly NIPA Series†	(2) Monthly and Finer Series§	(3) Monthly Series
Gross domestic product (GDP)	Personal consumption expenditures*	Producer price index of all finished goods
Investment*	Consumption of durable goods	Producer price index of capital equipment finished goods
Fixed investment (Residential construction, producer durable equipment, and private nonresidential construction)	Consumption of nondurable goods and services	Index of aggregate weekly hours worked by manufacturing workers
Change in business inventories*	Industrial production index	Retail sales of all goods
Government purchases*	Index of aggregate weekly hours worked by production workers on private nonfarm payrolls	Retail sales of durable goods
Federal government purchases	Civilian unemployment rate	Shipments of nondefense capital goods
State and local government purchases	Monetary base (Adjusted for changes in reserve requirements)	Real value of new private construction put in place
Net exports	M2 money supply	Total business inventories in constant dollars
	Federal funds rate	Total business inventories in current dollars
	10-year U.S. Treasury bond rate	Federal government payroll employment
	Consumer price index	Federal government outlays for national defense
	Standard & Poor's 500-stock price index	Industrial production index of defense and space equipment
		Real value of new state and local government construction put in place

†All the series in column (1) and the consumption series in column (2) are taken from the U.S. Department of Commerce's national income and product accounts (NIPA). Sources of series in other columns are listed in Table A1 in the Appendix.

§The series in column (2) are used by both models. Those series that are available more frequently than monthly are turned into monthly averages for the monthly model, and monthly averages are turned into quarterly averages for the quarterly model.

*In the quarterly model, four NIPA series are determined by an identity rather than directly: Investment = Fixed investment + Change in business inventories; Change in business inventories = GDP – (Personal consumption expenditures + Fixed investment + Government purchases + Net exports); Government purchases = Federal government purchases + State and local government purchases; and Personal consumption expenditures = Consumption of durable goods + Consumption of nondurable goods and services.

Table 2

How Monthly Updating Affects Forecasts of the Current Quarter

Measures of Accuracy in Predicting the Current Quarter (Over 1979:1–1995:1) for a Quarterly Model With No Data for That Quarter and When Updated With Progressively More Data

Time Series and Type of Forecast	Type of Error Statistic: Theil *U*	Mean Absolute Error	Root Mean Squared Error†
GDP			
Quarterly Model Forecast With No Current-Quarter Data	.805	2.216	2.942
Combined Forecast With Data for			
One Month	.647	1.838	2.366*
Two Months	.465	1.284	1.698***
Three Months	.459	1.293	1.678***
Consumption of Durable Goods			
Quarterly Model Forecast With No Current-Quarter Data	.600	10.293	12.683
Combined Forecast With Data for			
One Month	.761	12.161	16.081
Two Months	.417	6.581	8.812*
Three Months	.214	2.957	4.523*
Federal Government Purchases			
Quarterly Model Forecast With No Current-Quarter Data	.732	6.162	7.604
Combined Forecast With Data for			
One Month	.701	5.908	7.278*
Two Months	.755	6.517	7.835
Three Months	.751	6.476	7.794
Civilian Unemployment Rate			
Quarterly Model Forecast With No Current-Quarter Data	.699	.193	.245
Combined Forecast With Data for			
One Month	.375	.101	.131**
Two Months	.129	.039	.045***
Three Months	.000	.000	.000***
Consumer Price Index			
Quarterly Model Forecast With No Current-Quarter Data	.842	1.481	1.892
Combined Forecast With Data for			
One Month	.647	1.157	1.455**
Two Months	.393	.628	.884***
Three Months	.130	.222	.293***

† For the root mean squared errors, Christiano's (1989, pp.16–17) test for statistically significant differences between the quarterly model forecasts and the combined model forecasts finds these, as noted above:

* = Significant at the 90 percent level.
** = Significant at the 95 percent level.
*** = Significant at the 99 percent level.

Sources of basic data: U.S. Departments of Commerce and Labor

Table 3

How Monthly Updating Affects Forecasts of the Next Quarter—by Conditioning the Quarterly Model's Forecasts . . .

Measures of Accuracy in Predicting the Next Quarter
(Over 1989:1–1995:1) for a Quarterly Model With No Data for That Quarter
and When Its Forecasts Are Conditioned on the Best Combined Forecasts
for the Current Quarter, Updated With Progressively More Data

Time Series and Type of Quarterly Model Forecast	Type of Error Statistic		
	Theil *U*	Mean Absolute Error	Root Mean Squared Error†
GDP			
Forecast With No Current-Quarter Data	.885	1.847	2.343
Forecast Conditioned on Combined Current-Quarter Forecast With Data for			
One Month	.798	1.686	2.114
Two Months	.765	1.596	2.027*
Three Months	.743	1.510	1.969*
Consumption of Durable Goods			
Forecast With No Current-Quarter Data	.910	8.034	9.402
Forecast Conditioned on Combined Current-Quarter Forecast With Data for			
One Month	.927	8.240	9.572
Two Months	.905	7.667	9.343*
Three Months	.900	7.657	9.296
Federal Government Purchases			
Forecast With No Current-Quarter Data	.665	6.331	7.573
Forecast Conditioned on Combined Current-Quarter Forecast With Data for			
One Month	.691	6.748	7.867
Two Months	.692	6.963	7.875
Three Months	.713	7.017	8.113
Civilian Unemployment Rate			
Forecast With No Current-Quarter Data	.919	.370	.464
Forecast Conditioned on Combined Current-Quarter Forecast With Data for			
One Month	.543	.215	.274
Two Months	.451	.181	.228*
Three Months	.434	.181	.219*
Consumer Price Index			
Forecast With No Current-Quarter Data	.952	1.311	1.686
Forecast Conditioned on Combined Current-Quarter Forecast With Data for			
One Month	.931	1.173	1.647
Two Months	.935	1.289	1.654
Three Months	.894	1.229	1.583

† For the root mean squared errors, Christiano's (1989, pp.16–17) test for statistically significant differences between the quarterly model forecasts and the combined model forecasts finds these, as noted above:

* = Significant at the 90 percent level.
** = Significant at the 95 percent level.
*** = Significant at the 99 percent level.

Sources of basic data: U.S. Departments of Commerce and Labor

Table 4

. . . And by Combining Monthly and Quarterly Model Forecasts

Measures of Accuracy in Predicting the Next Quarter (Over 1989:1–1995:1) for a Quarterly Model When Its Forecasts Are Combined With Those of a Monthly Model, Updated With Progressively More Data

Time Series and Number of Months of Current-Quarter Data Available	Type of Error Statistic		
	Theil *U*	Mean Absolute Error	Root Mean Squared Error†
GDP			
One Month	.827	1.731	2.190
Two Months	.760	1.599	2.013
Three Months	.900	1.861	2.384
Consumption of Durable Goods			
One Month	.891	7.846	9.203
Two Months	.851	7.573	8.786
Three Months	.854	7.603	8.818
Federal Government Purchases			
One Month	.790	7.405	8.993
Two Months	.787	7.049	8.960
Three Months	.789	7.042	8.974
Civilian Unemployment Rate			
One Month	.547	.216	.276
Two Months	.444	.180	.224
Three Months	.418	.179	.211
Consumer Price Index			
One Month	.913	1.172	1.616
Two Months	.924	1.244	1.636
Three Months	.871	1.229	1.541

† For the root mean squared errors, Christiano's (1989, pp.16–17) test finds no statistically significant differences between the quarterly model forecasts and the combined model forecasts.

Sources of basic data: U.S. Departments of Commerce and Labor

Table 5

A Real-Time Test

Error Statistics for the *Blue Chip* and the Combined Model Methods in Forecasting 1990:1–1995:3, Using Progressively More Data Available in the Current Quarter

Time Series and Forecasting Method	Type of Error Statistic and Number of Months of Current-Quarter Data								
	Mean Error			Mean Absolute Error			Root Mean Squared Error†		
	One	Two	Three	One	Two	Three	One	Two	Three
GDP									
Blue Chip	.00	–.11	–.08	1.07	.97	.83	1.28	1.13	.99
Combined Models	–.43	.10	.10	1.04	.99	.92	1.36	1.34	1.15
Civilian Unemployment Rate									
Blue Chip	.04	.03	.01	.13	.11	.04	.17	.14	.07
Combined Models	.03	–.01	.00	.10	.03	.00	.13	.07	.00
Consumer Price Index									
Blue Chip	.10	.11	.03	.76	.51	.45	1.04	.70	.56
Combined Models	.23	–.11	–.03	1.00	.54	.26	1.32	.67	.36

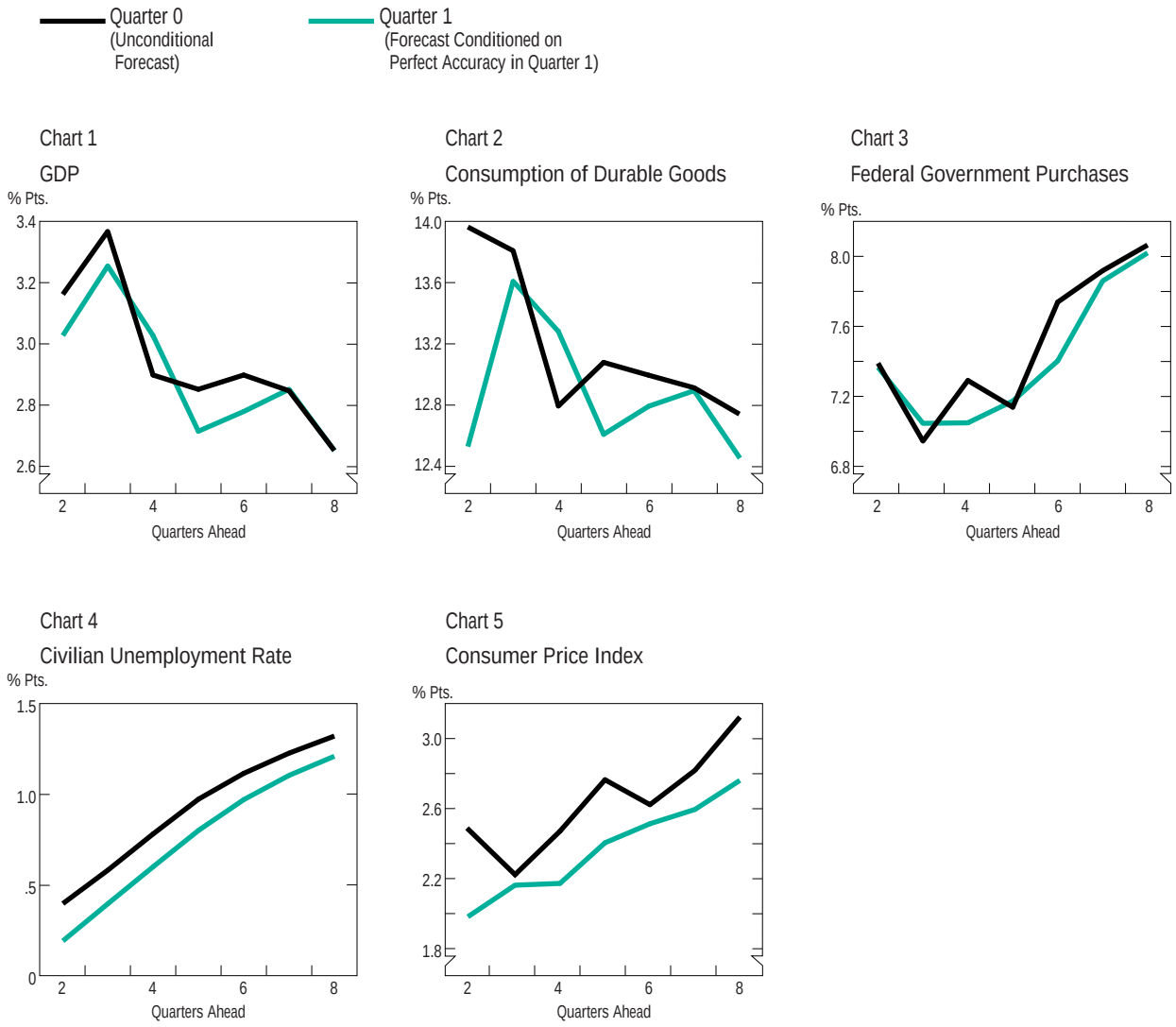
† For the root mean squared errors, Christiano's (1989, pp.16–17) test finds no statistically significant differences between the *Blue Chip* forecasts and the combined model methods.

Sources of basic data: *Blue Chip Economic Indicators*, various dates; U.S. Departments of Commerce and Labor

Charts 1–5

How Getting the Current Quarter Right Could Help a Model Predict Future Quarters

Root Mean Squared Errors of a Quarterly Model Predicting Eight Quarters Ahead
With Actual Data Through Quarter 0 or Quarter 1

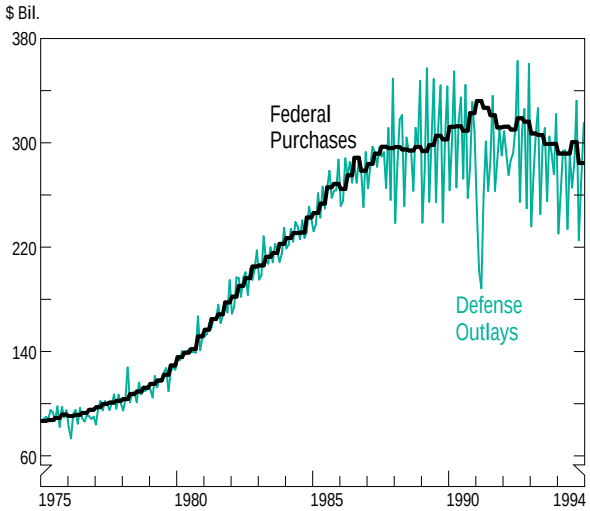


Sources of basic data: U.S. Departments of Commerce and Labor

Chart 6

Why Monthly Data Don't Help Forecast Federal Government Purchases

Quarterly Levels of Total Federal Government Purchases and Monthly Levels of National Defense Outlays, 1975–94



Source: U.S. Departments of Commerce and the Treasury

Charts 7–11

Another Look at How Monthly Updating Affects Forecasts of the Current Quarter

Cumulative One-Step-Ahead Absolute Forecast Errors; Quarterly, 1979:1–1995:1

Quarterly Model Forecast With No Current-Quarter Data

Combined Forecast With Current-Quarter Data for

- One Month
- Two Months
- Three Months

Chart 7

GDP

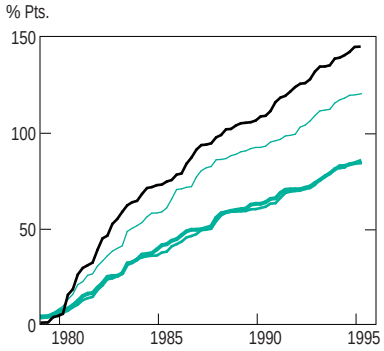


Chart 8

Consumption of Durable Goods

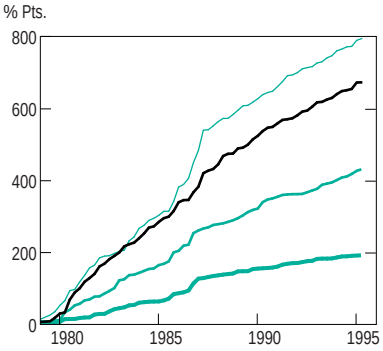


Chart 9

Federal Government Purchases

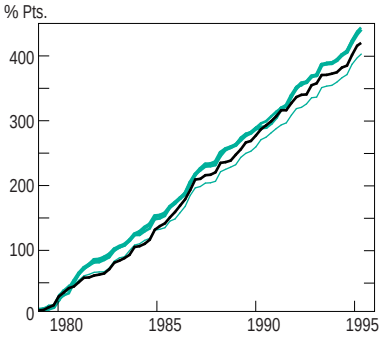


Chart 10

Civilian Unemployment Rate

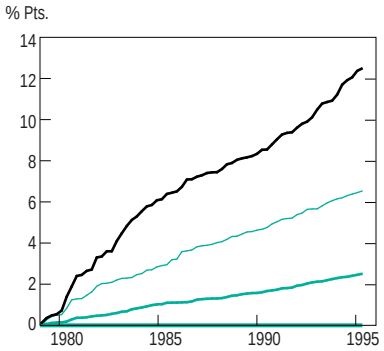
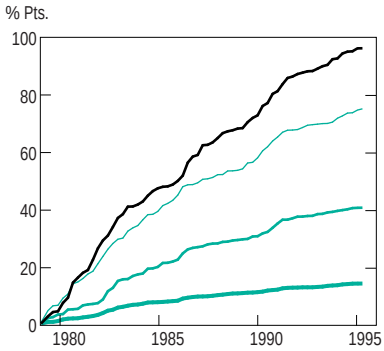


Chart 11

Consumer Price Index

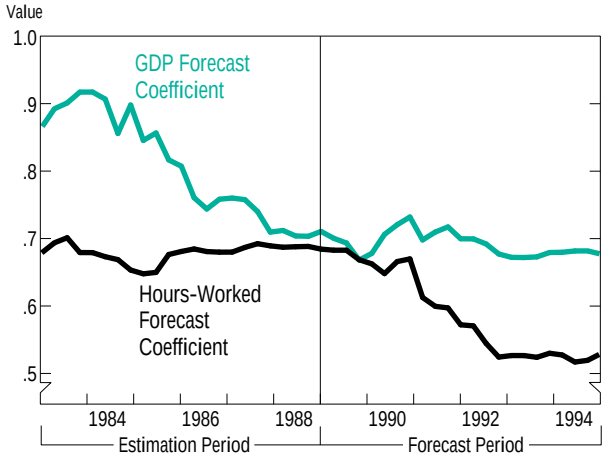


Sources of basic data: U.S. Departments of Commerce and Labor

Chart 12

Why the Next-Quarter Combined Forecasts Aren't Better

Coefficients on the Next-Quarter Forecasts of GDP and Hours Worked in the Equation for GDP; Quarterly, 1983:4–1994:4*



*The sample period is 1979:2–1994:4.
Sources of basic data: U.S. Departments of Commerce and Labor

Table A1

The Monthly Series in the Models

Sector	Code	Time Series	Primary Source
Production	*IP*	Industrial production index	Federal Reserve Board of Governors
	IPDS	Industrial production index of defense and space equipment	Federal Reserve Board of Governors
	HOURS	Index of aggregate weekly hours worked by production workers on private nonfarm payrolls	U.S. Department of Labor, Bureau of Labor Statistics
	HOURSM	Index of aggregate weekly hours worked by manufacturing workers	U.S. Department of Labor, Bureau of Labor Statistics
	UNEMP	Civilian unemployment rate	U.S. Department of Labor, Bureau of Labor Statistics
Nominal	*MB*	Monetary base	Federal Reserve Board of Governors
	M2	M2 money supply	Federal Reserve Board of Governors
	FF	Federal funds rate	Federal Reserve Board of Governors
	TBOND	10-year U.S. Treasury bond rate	Federal Reserve Board of Governors
	CPI	Consumer price index	U.S. Department of Labor, Bureau of Labor Statistics
	SP500	Standard & Poor's 500-stock price index	Standard & Poor's Corporation
	PPI	Producer price index of all finished goods	U.S. Department of Labor, Bureau of Labor Statistics
	PPICG	Producer price index of capital equipment finished goods	U.S. Department of Labor, Bureau of Labor Statistics
Other	*C*	Personal consumption expenditures	U.S. Department of Commerce, Bureau of Economic Analysis
	CD	Consumption of durable goods	U.S. Department of Commerce, Bureau of Economic Analysis
	CND	Consumption of nondurable goods and services	U.S. Department of Commerce, Bureau of Economic Analysis
	RET	Retails sales of all goods	U.S. Department of Commerce, Bureau of the Census
	RETDUR	Retail sales of durable goods	U.S. Department of Commerce, Bureau of the Census
	SHIP	Shipments of nondefense capital goods	U.S. Department of Commerce, Bureau of the Census
	VNCP	Real value of new private construction put in place	U.S. Department of Commerce, Bureau of the Census
	TBIR	Total business inventories in constant dollars	U.S. Department of Commerce, Bureau of the Census
	TBI	Total business inventories in current dollars	U.S. Department of Commerce, Bureau of the Census
	GFEMP	Federal government payroll employment	U.S. Department of Labor, Bureau of Labor Statistics
	NATDEF	Federal government outlays for national defense	U.S. Department of the Treasury
	VNCSL	Real value of new state and local government construction put in place	U.S. Department of Commerce, Bureau of the Census

Table A 2

The NIPA Series in the Models

Code	Time Series
GDP	Gross domestic product
C	Personal consumption expenditures
CD	Consumption of durable goods
CND	Consumption of nondurable goods and services
I	Investment
FI	Fixed investment
CBI	Change in business inventories
G	Government purchases
GF	Federal government purchases
GSL	State and local government purchases
NX	Net exports

Source: U.S. Department of Commerce, Bureau of Economic Analysis

Table A3

The Estimation and Forecast Periods for GDP and Its Components

Time Series and Type of Period	First Period in Estimation or Forecast	
	One Step Ahead	Two Steps Ahead*
Consumption		
Estimation	January 1959	—
Forecast	January–March 1969	—
GDP		
Estimation	1st Quarter 1969	2nd Quarter 1979
Forecast	1st Quarter 1974	1st Quarter 1984
GDP Components		
Estimation	1st Quarter 1974	1st Quarter 1984
Forecast	1st Quarter 1979	1st Quarter 1989

*Two-step-ahead forecasts are produced using the best combined one-step-ahead forecasts as conditioning variables in the quarterly model.